MAOA-L carriers are better at making optimal financial decisions under risk

SUPPLEMENTARY MATERIALS

Cary Frydman[1], Colin Camerer[1,2], Peter Bossaerts[1,2,3], Antonio Rangel[1,2]

[1] HSS, California Institute of Technology

[2] CNS, California Institute of Technology

[3]SFI, Ecole Polytechnique Fédérale Lausanne

Estimation of advanced computational model. The advanced computational model is described by the following four equations:

1) $U(RO)=pg - \lambda(1-p)l$,
2) $U(CO)=CO$.
3) $Pr(\text{accept RO})=(1+\exp(-a^{+}(U(RO) - U(CO)))^{-1}$, if $U(RO)-U(CO)>=0$
4) $Pr(\text{accept RO})=(1+\exp(-a^{-}(U(RO) - U(CO)))^{-1}$, if $U(RO)-U(CO)< 0$

The first two equations describe the valuation process and the second pair of equations describes the probability with which subjects choose the option with the highest net expected utility.

We used maximum likelihood to estimate the parameter vector $\theta=(\lambda, a^{+}, a^{-})$ for each subject. This required maximizing the following likelihood function:

$$l(\theta \mid y,p) = \sum_{i=1}^{140} y_i \log(F(p,\theta)) + (1 - y_i)\log(1 - F(p,\theta))$$

where

$$F(p, \theta)=(1+\exp(-a^{+}(U(RO) - U(CO)))^{-1} , \quad \text{if } U(RO)-U(CO)>=0$$

$$F(p, \theta)=(1+\exp(-a^{-}(U(RO) - U(CO)))^{-1}, \quad \text{if } U(RO)-U(CO)<0,$$

i indexes the trial number, y indicates the response, p describes the design matrix of the behavioral task, and θ indicates the parameter vector to be estimated. We used the Nelder-Mead Simplex Method as implemented in Matlab 2008b to obtain point estimates for each parameter.

As described in the methods section, we failed to successfully estimate at least one parameters for 19 out of 83 subjects that comprise our effective sample size. 9 subjects were dropped due to insufficient variation in responses, which makes estimation impossible. 8 subjects were excluded because their behavior was random, in the sense of being unresponsive to the underlying valuations options. 2 were excluded for failing to satisfy the basic "rationality" constraint that when the expected utility of the risky option is higher than the certain option, the risky option should always be accepted. Table S8 describes the sample sizes and explanations for all analyses in the main text.

Estimation problems for randomless choice behavior. We failed to estimate parameters of the advanced computational phenotype for 9 subjects (6 MAOA-H and 3 MAOA-L) due to lack of

variation in observed choices. This type of complication arises when subjects always choose the highest value option without any noise, which corresponds to the case $a=\infty$. This makes parameter estimation impossible since the resulting choice behavior can be generated using any sufficiently large temperature parameter a. This leads to a flat likelihood function in this range of the temperature parameters that makes maximization of the likelihood function over this range infeasible. This type of complication is more severe for the advanced computational phenotype because estimation will fail if subjects respond without noise in either the positive *or* negative EU domain.

Estimation problems for random choice behavior. On the other end of the spectrum from noiseless choice performance is random behavior. We failed to estimate the parameters of 8 subjects (5 MAOA-H and 3 MAOA-L) due to this problem. In particular, for these subjects the maximum likelihood procedure generated a nonsensical negative estimate for either a^+ or a^-. This problem can arise when subjects' parameters induce valuations that lead to a positive net value for the risky option in only a small fraction of the 140 choice pairs, for which the subject responds sub-optimally within this small set of trials.

About the identification of the temperature parameters: a^+ and a^- . The introduction of two temperature parameters in the advanced model makes the estimation problem more difficult than in the basic model. The fundamental problem is illustrated in Fig. S1, which shows that the fraction of trials in which the risky option has a positive net utility decreases rapidly with λ, which makes it difficult to obtain precise estimates of a^+ and a^- . Intuitively, the econometric difficulty arises because the sample size of trials in the positive and negative EU domain is endogenously determined by λ. When λ takes on an extremely high (low) value, the sample size of the positive (negative) EU domain becomes very small, which induces highly imprecise estimates of all computational model parameters. This estimation problem is intensified when subjects respond using either random or purely randomless behavior, as described above.

Example of estimation problems. Here we show that the estimation problems described above can arise even with simulated data in which we know that the underlying computational model applies. Consider a hypothetical subject with λ=2.5, in which case only 23% of trials (33 of 140 trials) will have a positive net RO, $a^-=3$, and a^+ very large, so that she responds with noiseless

choice performance in the positive EU domain. We simulated choice data from this hypothetical subject and attempted to estimate parameters using both the basic and advanced computational model. For the basic computational model, the parameters are estimated correctly and the likelihood function is concave in a (Fig S4). However, when estimating the advanced computational phenotype, the maximization algorithm does not converge and terminates the search procedure prematurely at: $\lambda=2.38$, $a^{+}=386$, $a^{-}=208$. Fig S5 shows that this is because the likelihood function is not concave in a^{+}; the likelihood surface is flat in the a^{+} dimension, and there is a continuum of parameter values that fit the data equally well. This leads to a failed maximization procedure, and an inability to estimate the advanced computational model.

To compare this function with data generated from a subject who does not respond with noiselss choice performance, we generated a data set from another hypothetical subject with $\lambda=2.5$ and $a^{+}=a^{-}=3$. Because this hypothetical subject does not respond with noiseless choice performance in the positive EU domain, we are able to successfully estimate the advanced computational model. The likelihood function for this subject is plotted in Fig S6, which shows the function is concave in both dimensions, allowing for successful maximization.

Fig. S1. Number of experimental trials in which the RO had positive and negative net EU as a function of the underlying loss aversion parameter.

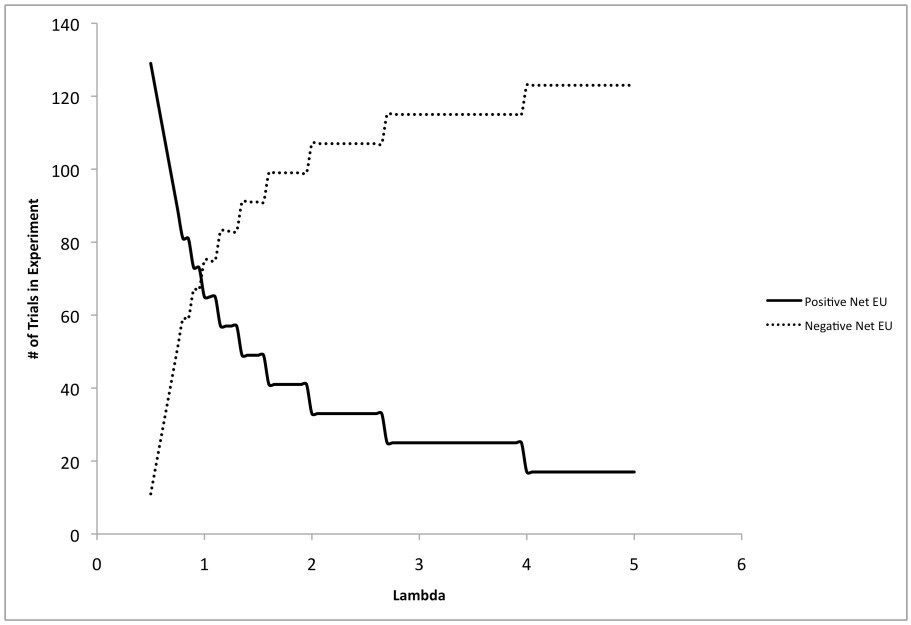

Fig. S2. MLE estimates of the loss aversion parameter under the basic and advanced computational models.

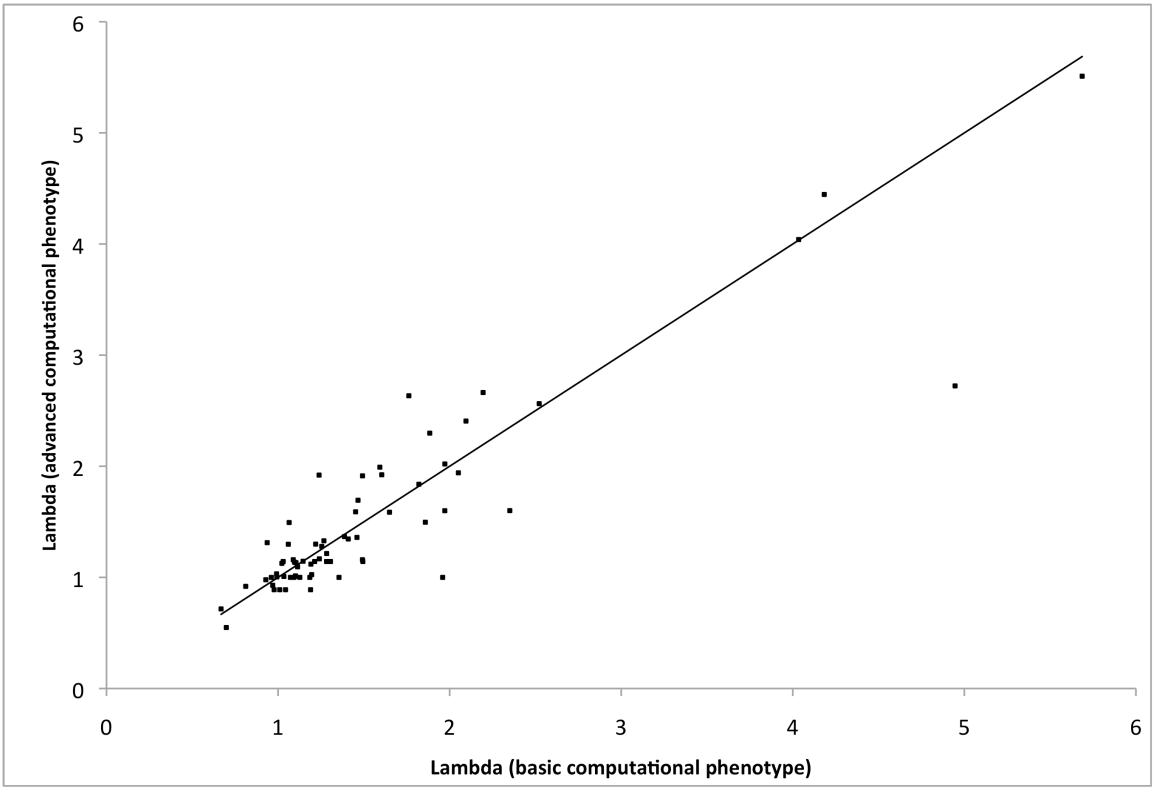

Fig. S3. Distribution of individual loss aversion estimates under the advanced computational phenotype.

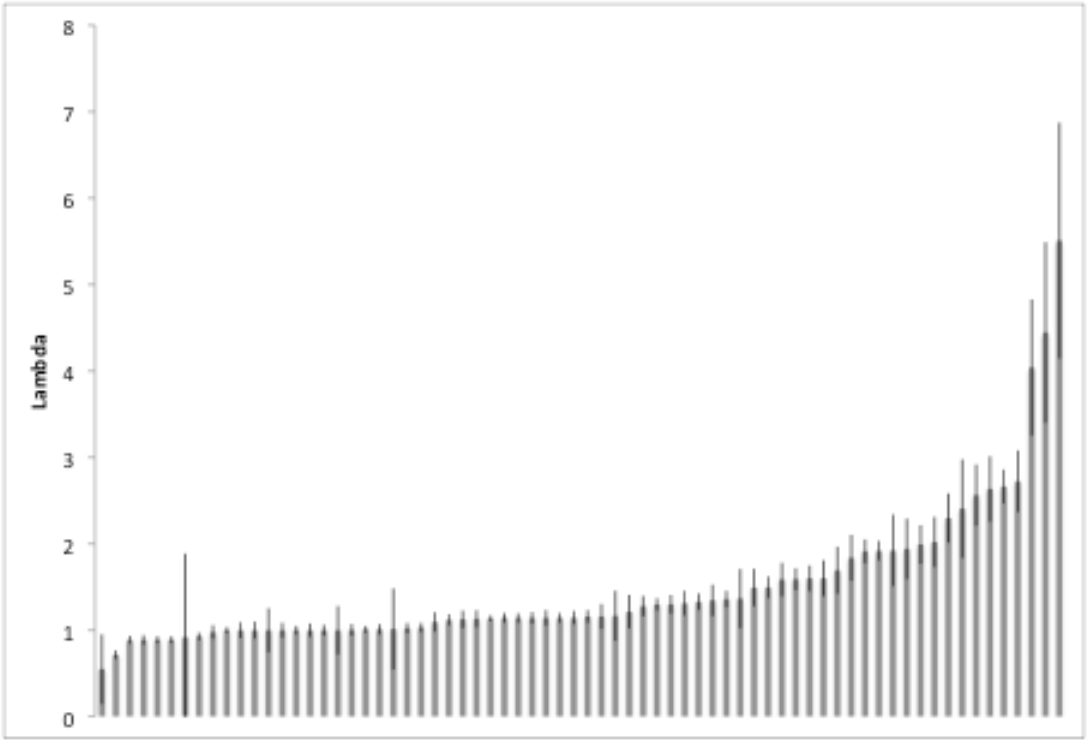

Fig. S4. Log-likelihood function of basic computational model. Choice data is simulated from hypothetical subject with $\lambda=2.5$, $a^{-}=3$, and noiseless choice performance in positive EU domain. The likelihood function is plotted at $\lambda=2.5$. The function is concave, allowing for maximization and successful estimation of the basic computational model.

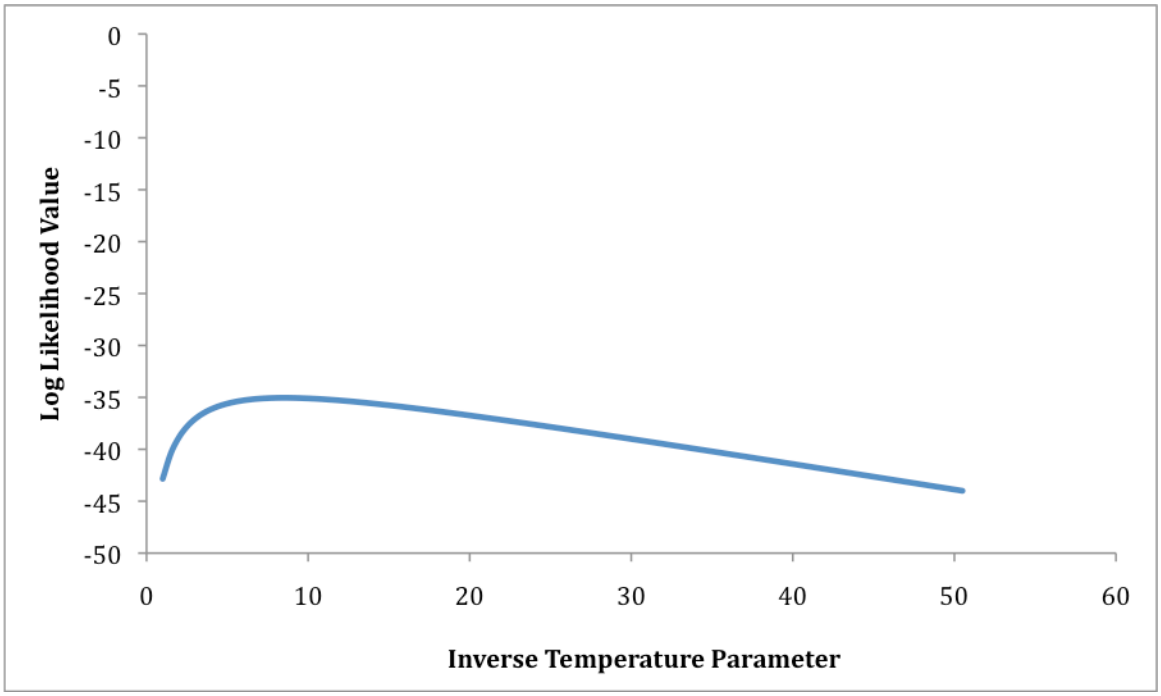

Fig. S5. Log-likelihood function of advanced computational model. Choice data is simulated from hypothetical subject with $\lambda=2.5$, $a^{-}=3$, and noiseless choice performance in positive EU domain. The likelihood function is plotted at $\lambda=2.5$. The function is flat in the a^{+} dimension, because of the noiseless choice performance in the positive EU domain. This causes the maximization of the log-likelihood function to fail, and leads to estimation problems for the a^{-} parameter as well.

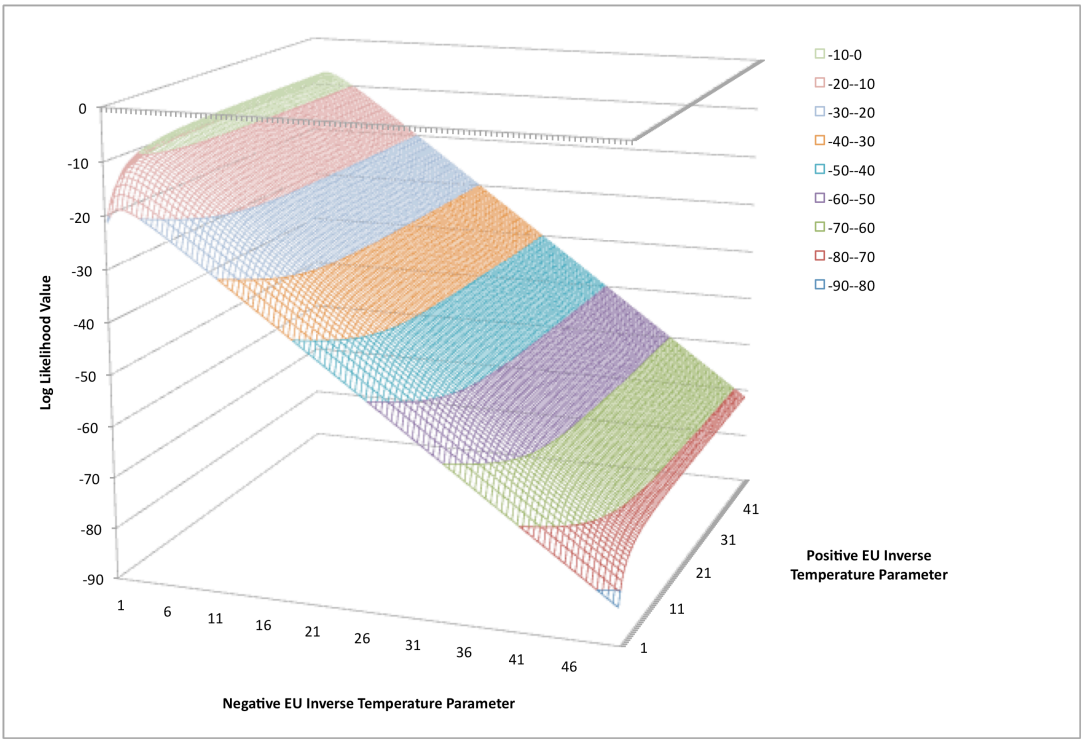

Fig. S6. Log-likelihood function of advanced computational model. Choice data is simulated from hypothetical subject with $\lambda=2.5$, $a^{+}=a^{-}=3$. The likelihood function is plotted at $\lambda=2.5$. The function is concave in both the $a^{+}$and a^{-} dimensions, which allows for successful estimation. The region that maximizes the log-likelihood function is depicted in orange.

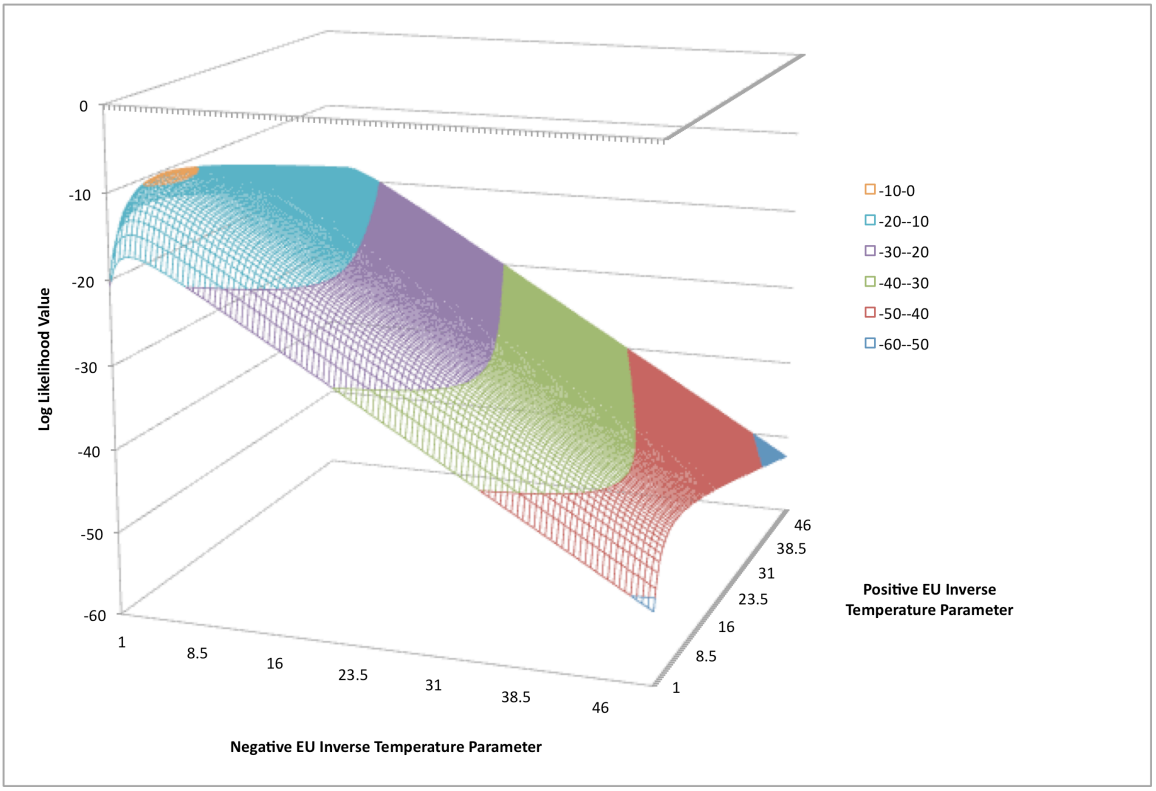

Table S1. Binary choices used in the experiment. CO indicates certain option.

Gain	Loss	CO	Gain	Loss	CO	Gain	Loss	CO
$12.00	-$24.00	$0.00	$2.00	-$3.50	$0.00	$4.00	-$1.50	$0.00
$12.00	-$22.50	$0.00	$4.00	-$5.50	$0.00	$5.00	-$2.50	$0.00
$10.00	-$20.00	$0.00	$6.00	-$7.50	$0.00	$10.00	-$7.50	$0.00
$9.00	-$18.00	$0.00	$12.00	-$13.50	$0.00	$4.00	-$1.00	$0.00
$12.00	-$21.00	$0.00	$2.00	-$3.25	$0.00	$6.00	-$3.00	$0.00
$10.00	-$18.75	$0.00	$5.00	-$6.25	$0.00	$8.00	-$5.00	$0.00
$8.00	-$16.00	$0.00	$10.00	-$11.25	$0.00	$12.00	-$9.00	$0.00
$9.00	-$16.88	$0.00	$9.00	-$10.13	$0.00	$5.00	-$1.88	$0.00
$10.00	-$17.50	$0.00	$2.00	-$3.00	$0.00	$9.00	-$5.63	$0.00
$12.00	-$19.50	$0.00	$4.00	-$5.00	$0.00	$5.00	-$1.25	$0.00
$8.00	-$15.00	$0.00	$8.00	-$9.00	$0.00	$6.00	-$2.25	$0.00
$9.00	-$15.75	$0.00	$2.00	-$2.75	$0.00	$10.00	-$6.25	$0.00
$10.00	-$16.25	$0.00	$6.00	-$6.75	$0.00	$8.00	-$4.00	$0.00
$6.00	-$12.00	$0.00	$5.00	-$5.63	$0.00	$6.00	-$1.50	$0.00
$8.00	-$14.00	$0.00	$2.00	-$2.50	$0.00	$9.00	-$4.50	$0.00
$12.00	-$18.00	$0.00	$4.00	-$4.50	$0.00	$12.00	-$7.50	$0.00
$9.00	-$14.63	$0.00	$2.00	-$2.25	$0.00	$8.00	-$3.00	$0.00
$6.00	-$11.25	$0.00	$2.00	-$2.00	$0.00	$10.00	-$5.00	$0.00
$5.00	-$10.00	$0.00	$4.00	-$4.00	$0.00	$9.00	-$3.38	$0.00
$8.00	-$13.00	$0.00	$5.00	-$5.00	$0.00	$8.00	-$2.00	$0.00
$10.00	-$15.00	$0.00	$6.00	-$6.00	$0.00	$12.00	-$6.00	$0.00
$6.00	-$10.50	$0.00	$8.00	-$8.00	$0.00	$10.00	-$3.75	$0.00
$9.00	-$13.50	$0.00	$9.00	-$9.00	$0.00	$9.00	-$2.25	$0.00
$12.00	-$16.50	$0.00	$10.00	-$10.00	$0.00	$10.00	-$2.50	$0.00
$5.00	-$9.38	$0.00	$12.00	-$12.00	$0.00	$12.00	-$4.50	$0.00
$4.00	-$8.00	$0.00	$2.00	-$1.75	$0.00	$12.00	-$3.00	$0.00
$8.00	-$12.00	$0.00	$2.00	-$1.50	$0.00	$2.00	$0.00	$1.00
$5.00	-$8.75	$0.00	$4.00	-$3.50	$0.00	$3.00	$0.00	$1.00
$6.00	-$9.75	$0.00	$5.00	-$4.38	$0.00	$4.00	$0.00	$2.00
$10.00	-$13.75	$0.00	$2.00	-$1.25	$0.00	$5.00	$0.00	$2.00
$4.00	-$7.50	$0.00	$6.00	-$5.25	$0.00	$7.00	$0.00	$3.00
$9.00	-$12.38	$0.00	$2.00	-$1.00	$0.00	$8.00	$0.00	$3.00
$5.00	-$8.13	$0.00	$4.00	-$3.00	$0.00	$12.00	$0.00	$6.00
$4.00	-$7.00	$0.00	$8.00	-$7.00	$0.00	$12.00	$0.00	$5.00
$6.00	-$9.00	$0.00	$9.00	-$7.88	$0.00	$12.00	$0.00	$4.00
$8.00	-$11.00	$0.00	$2.00	-$0.75	$0.00	$13.00	$0.00	$5.00
$12.00	-$15.00	$0.00	$5.00	-$3.75	$0.00	$13.00	$0.00	$6.00
$4.00	-$6.50	$0.00	$10.00	-$8.75	$0.00	$19.00	$0.00	$8.00
$5.00	-$7.50	$0.00	$2.00	-$0.50	$0.00	$22.00	$0.00	$10.00
$10.00	-$12.50	$0.00	$4.00	-$2.50	$0.00	$23.00	$0.00	$10.00
$6.00	-$8.25	$0.00	$6.00	-$4.50	$0.00	$25.00	$0.00	$9.00
$9.00	-$11.25	$0.00	$12.00	-$10.50	$0.00	$25.00	$0.00	$10.00
$2.00	-$4.00	$0.00	$5.00	-$3.13	$0.00	$26.00	$0.00	$10.00
$4.00	-$6.00	$0.00	$4.00	-$2.00	$0.00	$26.00	$0.00	$12.00
$8.00	-$10.00	$0.00	$8.00	-$6.00	$0.00	$28.00	$0.00	$13.00
$5.00	-$6.88	$0.00	$6.00	-$3.75	$0.00	$30.00	$0.00	$12.00
$2.00	-$3.75	$0.00	$9.00	-$6.75	$0.00			

Table S2. Individual parameter estimates in the basic computational model.

ID	λ	a
1	2.35 ±0.37	0.72 ±0.23
2	1.76 ±0.16	1.16 ±0.29
3	0.99 ±0.04	2.65 ±0.66
4	4.94 ±1.49	0.72 ±0.44
5	1 ±0.04	2.77 ±0.72
6	0.96 ±0.03	6.51 ±2.45
7	0.93 ±0.05	1.49 ±0.3
8	1.08 ±0.03	6.18 ±2.26
9	1.1 ±0.06	1.67 ±0.39
10	0.92 ±0.05	1.74 ±0.34
11	1.04 ±0.06	1.67 ±0.38
12	1.18 ±0.08	1.2 ±0.25
13	5.68 ±1.42	1.16 ±3.39
14	1.24 ±0.11	0.82 ±0.19
15	1.09 ±0.04	7.58 ±2.96
16	1.49 ±0.1	1.5 ±0.37
17	1.08 ±0.07	1.1 ±0.23
18	1.6 ±0.18	0.7 ±0.17
19	1.06 ±0.08	1.04 ±0.22
20	1.02 ±0.06	1.67 ±0.35
21	1.03 ±0.03	10.22 ±3.89
22	1.12 ±0.04	3.01 ±0.83
23	1.28 ±0.07	2.02 ±0.52
24	1.14 ±0.05	2.95 ±0.8
25	1.4 ±0.1	1.18 ±0.28
26	1.45 ±0.07	2.38 ±0.67
27	1.23 ±0.15	0.21 ±0.09
28	0.66 ±0.02	2.49 ±0.52
29	1.3 ±0.06	2.98 ±0.78
30	1.1 ±0.03	6.73 ±2.63
31	1.97 ±0.13	1.98 ±0.62
32	1.19 ±0.06	2.51 ±0.66
33	0.99 ±0.03	5.69 ±2.01
34	2.05 ±0.22	0.97 ±0.24
35	0.97 ±0.04	2.65 ±0.64
36	1.26 ±0.05	3.44 ±1.23
37	1.46 ±0.12	1.09 ±0.24
38	4.18 ±0.62	3.73 ±18.9
39	1.21 ±0.04	3.89 ±1.26
40	1.49 ±0.09	2.07 ±0.54
41	1.85 ±0.16	1.24 ±0.33
42	2.19 ±0.17	1.94 ±0.63
43	1.45 ±0.07	2.77 ±0.89
44	1.09 ±0.06	7.7 ±3.12
45	1.49 ±0.12	1.11 ±0.25
46	1.97 ±0.18	1.37 ±0.38
47	1.07 ±0.03	6.7 ±2.49
48	2.52 ±0.22	1.62 ±0.55
49	1.21 ±0.05	2.71 ±0.68
50	1.05 ±0.05	1.89 ±0.45
51	1.28 ±0.11	0.94 ±0.21
52	1.35 ±0.11	1 ±0.23
53	0.81 ±0.2	0.3 ±0.12
54	1.38 ±0.15	0.67 ±0.16
55	1.11 ±0.07	1.48 ±0.32
56	1.1 ±0.05	0.7 ±0.22
57	1.95 ±0.36	0.48 ±0.15
58	0.69 ±0.01	0.86 ±3.69
59	2.09 ±0.13	0.65 ±0.13
60	1.02 ±0	4.39 ±0.77
61	1.88 ±1.44	1.03 ±0.36
62	1.08 ±0	14.13 ±0
63	1.25 ±0.15	1.74 ±0.42
64	0.96 ±0.29	2.53 ±7.34

Table S3. Individual parameter estimates for advanced computational phenotype

ID	λ	a^+	a^-
1	1.6 ±0.2	0.27 ±0.22	>100 ±14.25
2	2.63 ±0.37	15.61 ±9.13	0.43 ±0.15
3	1 ±0.06	2.92 ±4.17	2.35 ±3.61
4	2.72 ±0.35	0.31 ±0.34	13.16 ±10.33
5	0.88 ±0.04	1.86 ±0.77	>100 ±2.13
6	0.99 ±0.03	>100 ±15.19	4.16 ±6.37
7	1.31 ±0.14	5.51 ±10.79	0.47 ±1.1
8	1 ±0.08	3.99 ±2.03	>100 ±0.4
9	1.13 ±0.09	2.06 ±3.32	1.35 ±1.6
10	0.97 ±0.07	2.38 ±0.98	1.22 ±1.99
11	0.88 ±0.04	1.12 ±0.33	>100 ±4.21
12	0.88 ±0.05	0.7 ±0.24	>100 ±6.15
13	5.5 ±1.36	1.14 ±0.71	1.26 ±15.26
14	1.16 ±0.29	0.63 ±3.41	1.16 ±0.7
15	1.13 ±0.03	33.74 ±15.31	5.1 ±4.2
16	1.15 ±0.07	0.9 ±0.34	36.11 ±13.49
17	1.15 ±0.14	1.35 ±1.83	0.84 ±2.23
18	1.92 ±0.41	1.25 ±1.58	0.45 ±0.43
19	1.49 ±0.21	3.04 ±6.95	0.39 ±1.08
20	1.12 ±0.1	2.77 ±4.76	1.02 ±0.74
21	1 ±0.04	8.25 ±4.7	34.44 ±13.85
22	1 ±0.05	2.05 ±0.87	>100 ±2.96
23	1.14 ±0.05	1.38 ±0.49	>100 ±13.24
24	1.14 ±0.07	2.95 ±4.85	2.96 ±5.77
25	1.34 ±0.18	0.95 ±0.49	1.6 ±6.79
26	1.35 ±0.09	1.9 ±1.16	4.71 ±9.33
27	1.92 ±0.11	0.75 ±3.41	0.09 ±0.7
28	0.71 ±0.04	3.58 ±3.22	1.3 ±1.4
29	1.14 ±0.06	1.99 ±0.79	>100 ±4.69
30	1 ±0.05	4.02 ±1.41	>100 ±5.66
31	1.6 ±0.14	1.25 ±0.54	>100 ±5.21
32	1.02 ±0.06	1.62 ±0.57	>100 ±6.48
33	1.03 ±0.05	>100 ±8.21	3.4 ±2.35
34	1.94 ±0.35	0.77 ±0.45	1.24 ±6.18
35	0.88 ±0.04	1.86 ±0.73	>100 ±3.16
36	1.32 ±0.09	5.34 ±8.46	2.36 ±3.67
37	1.69 ±0.27	1.44 ±1.39	0.73 ±2.62
38	4.44 ±1.04	71.41 ±10.07	1.9 ±17.73
39	1.14 ±0.05	2.91 ±1.24	15.11 ±11.66
40	1.91 ±0.13	11.62 ±8.5	0.84 ±1.37
41	1.49 ±0.12	0.74 ±0.3	>100 ±12.6
42	2.66 ±0.19	>100 ±8.19	0.96 ±1.52
43	1.58 ±0.12	6.77 ±10.87	1.63 ±1.44
44	1 ±0.27	4.62 ±1.87	>100 ±0.78
45	1.14 ±0.08	0.64 ±0.25	>100 ±8.72
46	2.02 ±0.29	1.6 ±2.26	1.19 ±3.79
47	1 ±0.07	4.62 ±1.73	>100 ±2.17
48	2.56 ±0.35	1.97 ±1.96	1.39 ±3.65
49	1.29 ±0.1	3.81 ±7.11	1.89 ±3.58
50	1.29 ±0.07	12.41 ±15.4	0.94 ±0.35
51	1.21 ±0.19	0.69 ±0.33	1.38 ±4.64
52	1 ±0.09	0.63 ±0.2	3.16 ±8.03
53	0.91 ±0.96	0.37 ±2.7	0.16 ±6.06
54	1.36 ±0.34	0.65 ±0.91	0.7 ±2.44
55	1.09 ±0.11	1.39 ±0.53	1.64 ±4.11
56	1.01 ±0.47	0.55 ±1.81	1.04 ±5.21
57	1 ±0.25	0.14 ±0.16	2.49 ±5.78
58	0.54 ±0.4	0.65 ±1.69	9.25 ±8.63
59	2.4 ±0.57	0.99 ±0.91	0.47 ±1.63
60	1.14 ±0.05	>100 ±3.67	2.16 ±1.3
61	2.29 ±0.28	5.55 ±7.16	0.56 ±0.27
62	1 ±0.06	7.94 ±3.27	>100 ±0.61
63	1.27 ±0.11	1.96 ±1.86	1.53 ±3.34
64	0.92 ±0.04	2.93 ±2.73	6.43 ±8.76

Tables S4. Allelic and genotype frequencies for 5HTT and MAOA for sample used in basic behavioral results (N=83). "s" indicates the short allele of the 5HTT gene. MAOA-L (MAOA-H) indicates the low (high) variant of the MAOA gene.

A)

5HTT	**N**	**%**
Allele		
S	83	50.00%
L	83	50.00%
Genotype		
s/s	23	27.38%
s/l	37	44.05%
l/l	23	27.38%

B)

MAOA	**N**	**%**
Allele (bp-repeats)		
3	35	42.17%
3.5	1	1.20%
4	46	55.42%
5	1	1.20%
Genotype		
MAOA-L	36	43.37%
MAOA-H	47	56.63%

Table S5. Allelic and genotype frequencies for DRD4 sample used in basic behavioral results (N=83). 7+ denotes a carrier of the 7-repeat allele.

DRD4		
Allele	N	%
2	17	10.24%
3	7	4.22%
4	97	58.43%
5	4	2.41%
7	40	24.10%
8	1	0.60%
Genotype		
2/2	1	1.20%
2/3	1	1.20%
2/4	8	9.64%
2/7	6	7.23%
3/4	3	3.61%
3/7	3	3.61%
4/4	30	36.14%
4/5	4	4.82%
4/7	21	25.30%
4/8	1	1.20%
7/7	5	6.02%
7+	**35**	**42.17%**
7-	**48**	**57.83%**

Tables S6. Allelic and genotype frequencies for 5HTT and MAOA for sample used in basic and advanced computational phenotype analyses (N=64). "s" indicates the short allele of the 5HTT gene. MAOA-L (MAOA-H) indicates the low (high) variant of the MAOA gene.

A)

5HTT	**N**	**%**
Allele		
S	66	51.56%
L	62	48.44%
Genotype		
s/s	18	28.13%
s/l	30	46.88%
l/l	16	25.00%

B)

MAOA	**N**	**%**
Allele (bp-repeats)		
3	28	43.75%
3.5	0	0.00%
4	35	54.69%
5	1	1.56%
Genotype		
MAOA-L	29	45.31%
MAOA-H	35	54.69%

Table S7. Allelic and genotype frequencies for DRD4 for sample used in basic and advanced computational phenotype analyses (N=64). 7+ denotes a carrier of the 7-repeat allele.

DRD4		
Allele	N	%
2	14	10.94%
3	5	3.91%
4	73	57.03%
5	3	2.34%
7	32	25.00%
8	1	0.78%
Genotype		
2/2	1	1.56%
2/3	1	1.56%
2/4	6	9.38%
2/7	5	7.81%
3/4	2	3.13%
3/7	2	3.13%
4/4	23	35.94%
4/5	3	4.69%
4/7	15	23.44%
4/8	1	1.56%
7/7	5	7.81%
7+	**27**	**42.19%**
7-	**37**	**57.81%**

Table S8. Summary of sample sizes. "Basic behavioral results" refers to results from analysis shown in Fig 1. "Basic & advanced computational phenotype" refers to results from all behavioral and genetic analyses using either the basic (2 parameter) or advanced (3 parameter) computational phenotype.

Initial Sample Size	**90**
Failure to genotype	6
Failure to understand instructions	1
Basic behavioral results sample size	**83**
Randomless Choice Behavior	9
Random Choice Behavior	8
Violate rationality constraint	2
Failure to estimate basic or advanced computational phenotype	19
Basic & Advanced computational phenotype sample size	**64**